"Real-time digital contact tracing: Development of a system to control COVID-19 outbreaks in nursing homes and long-term care facilities"

Jerry Wilmink, Ilyssa Summer, David Marsyla, Subhashree Sukhu, Jeffrey Grote, Greg Zobel, Howard Fillit, Satish Movva

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Corresponding Author:
Jerry WilminkPhD, MBA,
Phone: +16153644985
Email: jwilmink@carepredict.com

Abstract

Background: Severe acute respiratory syndrome-coronavirus 2 (SARS-CoV-2) can spread rapidly in nursing homes and long term care (LTC) facilities. Symptoms-based screening and manual contact tracing have limitations that render them ineffective for containing viral spread in LTC facilities: (i) symptoms-based screening alone cannot identify asymptomatic infected persons; (ii) viral spread is too fast in confined living quarters to be contained by slow manual contact tracing processes.

Objective: We describe the development and implementation of a digital contact tracing system that LTC facilities can use to rapidly identify, isolate and then test asymptomatic and symptomatic infected contacts. Computer simulation models were also developed to assess the performance of the system versus conventional containment methods.

Methods: We developed a stochastic transmission model parameterized specifically for COVID-19 in LTC facilities. Using various scenarios we used the model to quantify the effectiveness of several intervention groups to control outbreaks: no intervention, symptom mapping, PCR testing, manual contact tracing, and digital contact tracing.

Results: Our digital contact tracing system allows users to rapidly identify and then isolate close contacts, to store and track infection data in a respiratory line listing tool, and identify contaminated rooms. Our simulation results suggest that digital contact tracing allow for rapid and effective identification and containment of potentially infected contacts.

Conclusions: Digital contact tracing systems show promise as effective tool to control COVID-19 outbreaks. As facilities prepare to relax restrictions and re-open to outside visitors, such tools will allow them to do so in a surgical, cost-effective manner that both controls outbreaks while also safely giving residents back the life they once had before this pandemic hit. Clinical Trial: Not applicable

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Gerald J. Wilmink, PhD[1], Ilyssa Summer PhD[1], David Marsyla[1], Subhashree Sukhu[1], Jeffrey Grote[1], Greg Zobel[1], Howard M. Fillit, MD[2-3], Satish Movva[1]

1 – CarePredict Corporation, 324 South University Drive, Plantation, Florida 33324

2 –Department of Geriatric Medicine and Palliative Care, Icahn School of Medicine at Mount Sinai, 1 Gustave L. Levy Place, New York, NY 10029-5674

3 –Alzheimer's Drug Discovery Foundation, 57 West 57th Street, Suite 904, New York NY 10019

*Address correspondence -Gerald Wilmink, PhD, CarePredict Corporation, Plantation FL 33324,

E-mail: jwilmink@carepredict.com.

Abstract

Background: Severe acute respiratory syndrome-coronavirus 2 (SARS-CoV-2) can spread rapidly in nursing homes and long term care (LTC) facilities. Symptoms-based screening and manual contact tracing have limitations that render them ineffective for containing viral spread in LTC facilities: (i) symptoms-based screening alone cannot identify asymptomatic infected persons; (ii) viral spread is too fast in confined living quarters to be contained by slow manual contact tracing processes.

Objective: We describe the development of a digital contact tracing system that LTC facilities can use to rapidly identify and contain asymptomatic and symptomatic SARS-CoV-2 infected contacts. A compartmental model was also developed to simulate disease transmission dynamics and to assess system performance versus conventional methods.

Methods: We developed a compartmental model parameterized specifically to assess COVID-19 transmission in LTC facilities. The model was used to quantify the impact of asymptomatic transmission and to assess the performance of several intervention groups to control outbreaks: no intervention, symptom mapping, PCR testing, manual and digital contact tracing.

Results: Our digital contact tracing system allows users to rapidly identify and then isolate close contacts, store and track infection data in a respiratory line listing tool, and identify contaminated rooms. Our simulation results indicate that the speed and efficiency of digital contact tracing contributed to it's superior control performance compared to conventional controls methods.

Conclusions: Digital contact tracing systems show promise as effective tool to control COVID-19 outbreaks in LTC facilities. As facilities prepare to relax restrictions and re-open to outside visitors, such tools will allow them to do so in a surgical, cost-effective manner that both controls outbreaks while also safely giving residents back the life they once had before this pandemic hit.

Introduction

The coronavirus disease 2019 (COVID-19) is a rapidly spreading infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). [1] As of June 1, 2020, a total of 1.7 million cases and 103,000 COVID-19-associated fatalities have been reported in the U.S. [2] Despite representing only 0.7% of the total U.S. population, residents of nursing homes and LTC facilities account for 11% of cases and over 40% of all COVID-19 fatalities in the U.S. [2, 3] Residents in LTC facilities exhibit an infection fatality rate of 20%, a rate that is 14-times higher than for the total population. [2-5]

The vulnerability of LTC facilities to respiratory disease outbreaks is well documented, and several factors have contributed to the recent COVID-19 outcomes: (i) high-risk population – the majority of LTC residents are advanced in age and have one or more underlying comorbidities [6-10]; (ii) high-risk setting – the frequency, type, and duration of close contact between the residents and staff; (iii) epidemiological features and transmission dynamics – SARS-CoV-2 infected persons are infectious before showing symptoms and 40% of new COVID-19 cases are transmitted by asymptomatic cases. [11, 12] Due to these factors, symptoms-based monitoring and slow manual contact tracing methods presently used by LTC facilities have proven inadequate, and new tools are needed to better control COVID-19 outbreaks. [13-15]

Advanced age and underlying co-morbidities are well-established risk factors for severe COVID-19-associated illness, hospitalization, and death. [16, 17] Adults age 85 and older represent 2% of the U.S. population but contributed to 33% of all COVID-19 deaths. (**Supp. Figure 1**). [2] This death rate is 210.5 (per 100,000 population), 15-times higher than the overall population rate. [2, 18] The average COVID-19-associated hospitalization rate for adults age 85 and older is 396.4 (per 100,000 population), roughly 6-times higher than the overall population. Older adults are also disproportionally affected by chronic conditions, where 60% have two or more conditions, and such persons are known to be at an elevated risk for severe COVID-19-associated illness. [19, 20] Richardson *et al.* found that 94% of patients hospitalized with COVID-19 exhibited one comorbidity,

and 88% of patients exhibited two or more.[21]

In addition to housing vulnerable residents, LTC facilities exhibit several intrinsic characteristics that make them high-risk settings conducive for rapid spread of SARS-CoV-2.[22] First, in LTC facilities, residents live together in close quarters, eat communal meals, and participate in many group social activities. Second, caregiving staff frequently assist residents with their activities of daily living (ADL), such as bathing, dressing, and eating. ADL assistance requires intimate resident contact, which increases the probability for transmission from an infected staff member or resident. Third, during the course of a work day, facility staff move from room-to-room to provide care for many different residents. In addition, many staff members may work at multiple facilities or home care agencies, thus if they become infected they can serve as potential vectors between facilities.[13, 14, 23] Overall, the frequency, type, and duration of contact between residents and staff has contributed to increased SARS-CoV-2 transmission both within and between facilities.

The epidemiological features, infection progression characteristics, and transmission dynamics of SARS-CoV-2 and COVID-19 disease have also contributed to the difficulties faced by LTC facilities containing outbreaks. Such parameters are also fundamental to the development of accurate mathematical models, control systems, and effective infection control policies.[11, 16, 24-27] The SARS-CoV-2 virus is known to spread primarily person-to-person through small, droplets (> 5-10 µm) expelled when an infected symptomatic or asymptomatic person coughs, sneezes, or breathes. [11, 12] Airborne virus transmission may also be possible in confined environments, as in LTC facilities, because when an infected person speaks they can expel aerosols, tiny virus containing droplet nuclei (≤5 µm), that can linger in the air for up to 14 minutes.[28-31] SARS-CoV-2 is also believed to be viable and infectious on surfaces for hours, therefore transmission can occur indirectly via 'fomites' – contamination of surfaces in the environment.[32, 33]

Isolation of confirmed and suspected cases, and identification of contacts via contact tracing are crucial to effective control efforts. These methods hinge on three key epidemiological parameters: (i)

basic reproduction number (R_o) - the average number of secondary infections generated by each infection; (ii) serial interval – duration between successive infections and speed of viral spread; (iii) the proportion of asymptomatic transmission. Best estimates indicate that the R_o for SARS-CoV-2 causing COVID-19 is 2.5, which is significantly higher than the flu. [34] The serial interval, duration between symptom onset in a primary and secondary case, is estimated to be 3.96 days, which is almost twice as fast as SARS-CoV-1. [26, 27] The mean latent period, time from infection to onset of infectiousness, is estimated to be 3 days, which is shorter than the 5.1 day incubation period–time between infection and onset of symptoms (fever, cough, shortness of breath)(**Figure 1**). [11, 16, 24-27] Consequently, SARS-CoV-2 infected persons are most infectious 1-3 days before showing symptoms and up to 10 days after symptom onset. [16, 25] SARS-CoV-2 is transmitted via symptomatic, asymptomatic, and pre-symptomatic routes, and current, best estimates indicate the following: 25-81% of cases are asymptomatic [35, 36], symptomatic and asymptomatic cases are equally infectious [34], and 40-44% of new COVID-19 cases are transmitted from presymptomatic individuals. [7, 16, 34, 35, 37, 38] These features are consistent with early reports from LTC facilities, where 56-73% of residents that tested positive for COVID-19 were asymptomatic at the time of testing[13, 14, 39], and that both presymptomatic and asymptomatic cases contributed to rapid facility spread.[13-15] Thus, symptom-based screening alone failed to detect asymptomatic infectious cases. Arons *et al.* posited that conventional screening approaches in LTC facilities are inadequate because symptoms-based screening and PCR tests are only being performed on symptomatic persons. [13-15] LTC facilities need contact tracing systems to rapidly identify, contain and then broadly PCR test asymptomatic infectious contacts. [40]
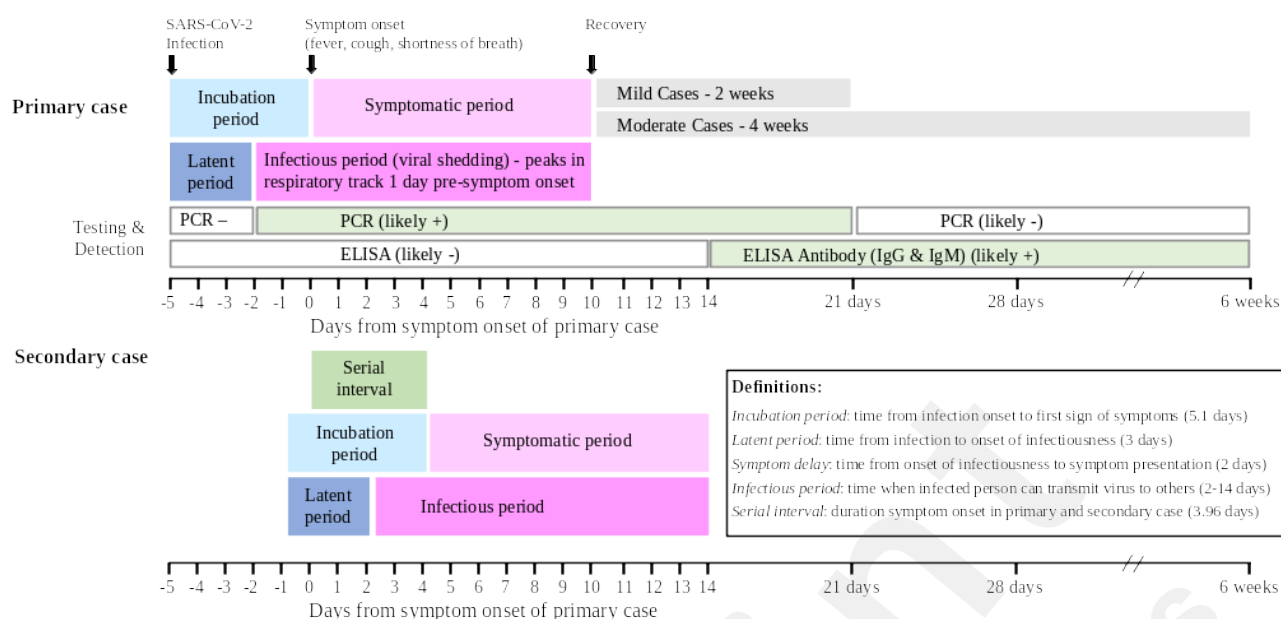
Figure 1. Overview of current estimates on key epidemiological features, infection characteristics, transmission dynamics, and testing methods for SARS-CoV-2 and COVID-19 disease. [11, 16, 24-27]

Contact tracing, a core disease control measure used by public health authorities to prevent the spread of infectious diseases, is now being employed to identify and isolate individuals that came in close contact with an SARS-CoV-2 infected persons.[41] The manual contact tracing process is slow and has inherent time delays between confirming a case and finding a person's contacts. [11, 42, 43] These time delays give secondary contacts more time to transmit the virus even further in the facility. Manual contact tracing also relies on humans both for data collection and data entry, which increases the potential for inaccurate or incomplete results due to human error. For the tracing process, a case needs to remember and report all contacts made over the past 14 days. In the LTC setting, an infected resident may have 10-30 close contacts, and older adults that may be suffering from memory impairment or dementia, may forget their close contacts. Since more than 70% of contacts must be traced in order to control an outbreak[44], this may be difficult to achieve using manual contact tracing in a LTC facility.

Since SARS-CoV-2 spreads too fast to be contained by slow manual contact tracing, several digital contact tracing tools using smartphone-based apps have recently been developed. [45, 46] If

widely adopted, these apps show promise to effectively mitigate the spread of SARS-CoV-2 for the general population; however, smartphone-based contact tracing may have limited utility in LTC facilities for several reasons. First, LTC residents are typically older adults, and only 17% of adults 80+ own a smartphone. [47] Second, staff in many LTC facilities are not permitted to use a smartphone during the work day. Finally, smartphone-based approaches use Bluetooth technology which transmits through thin walls in a facility and can result in false positives. Due to these limitations, there is benefit to having a digital contact tracing system built specifically for use in LTC facilities.

In this study we describe the development and implementation of an real-time digital contact tracing system designed specifically for LTC facilities to mitigate the spread of SARS-CoV-2 infections. Additionally, we developed a SEIR-type infectious model adopted and parameterized specifically to describe propagation of COVID-19 in LTC facilities. The model was also used to simulate and assess the interventional performance of digital contact tracing compared to symptom-based mapping, manual contact tracing, and PCR testing.

Methods

Real-time digital contract tracing system

The CarePredict PinPoint is a real-time digital contact tracing system designed for use in a LTC facility. The system can be used to rapidly identify and categorize individuals (staff, residents and visitors) that may have been exposed to a COVID-19 infected person. The system consists of a wrist-worn wearable device (Tempo™), beacons for real-time location tracking, and a cloud-based, software application for visualization of ego-centric contact networks (**Figure 2**).
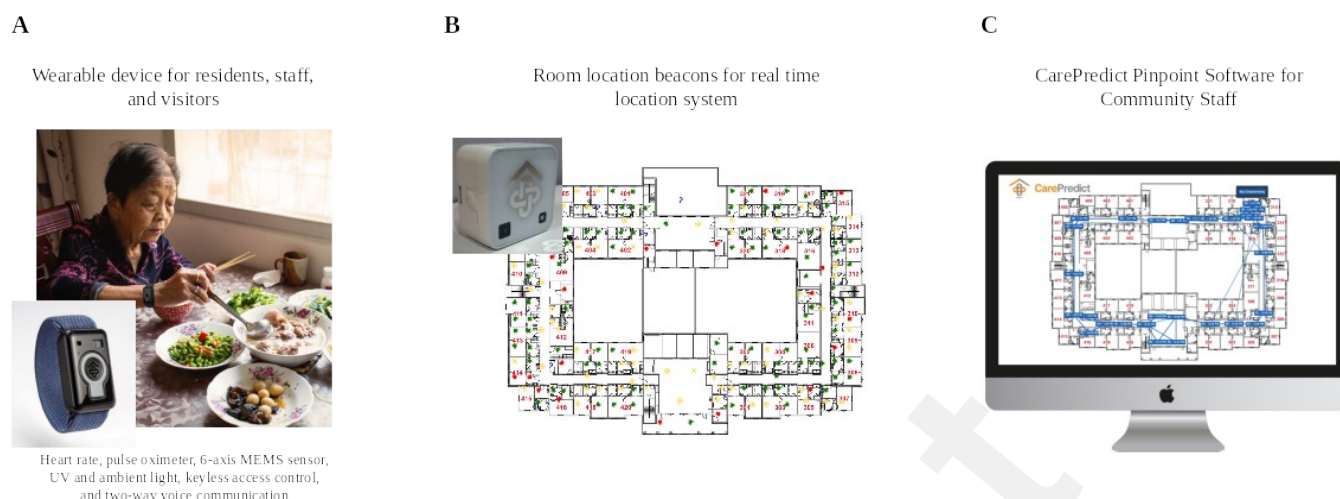
A

Wearable device for residents, staff, and visitors

Heart rate, pulse oximeter, 6-axis MEMS sensor, UV and ambient light, keyless access control, and two-way voice communication

B

Room location beacons for real time location system

C

CarePredict Pinpoint Software for Community Staff

Figure 2. Digital contact tracing system: wearable device, real-time location tracking, and software. A. Wearable device. B. Real-time location system for retrospective contact tracing. C. PinPoint software.

The wearable is worn on the dominant arm of residents, staff, and visitors. The wearable recognizes gestures according to the changes in the user's wrist kinematics and autonomously provides outputs on the user's ADLs, such as eating, bathing, walking, bathroom visits, and sleep duration. The wearable houses the following sensors for detection of the user's heart rate, blood oxygenation (via pulse oximetry), 6-axis MEMS sensor, and UV and ambient light sensors (**Figure 3A**). When coupled with data from context beacons, indoor positioning information is obtained such as the type of room in which the person is located. (**Figure 3B**). The wearable uses Wi-Fi to communicate data to the cloud over an encrypted connection, and supports two-way audio so the wearer can communicate via mobile apps on iOS and Android devices. The device supports RFID protocols for integration with electronic door access systems. The wearable measures 50 x 33 x 17.7 mm, weighs 40 grams, and includes a microprocessor, RFID, Bluetooth 4, and Wi-Fi 802.11 b/g/n. The wearable uses a 380mAH Li-ion 10.6g polymer battery, which has 50-100 hours of battery life. The device uses a swappable battery design so the user does not have to take off the device for charging. The wearable has an operational temperature range of -20°C to +55°C, water-resistant to IP67, and has the following certifications: FCC, CE, TELEC, RoHS, REACH, WEEE, Bluetooth.

The real-time location system uses beacons to determine the room-level indoor location of the wearable, and the duration of contact with other wearable devices. The beacon measures 52.1 x 52.1

x 28.0 mm, weighs 78 g, and uses Lithium CR123A batteries. A patented line-of-sight technology is

utilized for multi-floor level indoor positioning with room-level accuracy and no bleed-throughs.

The PinPoint software consists of three tools:

1. Contact tracing workspace: (i) Direct - identify all individuals the infected person (PUI) had

   direct contact with in the facility; (ii) Secondary or indirect contacts - individuals who

   subsequently came in contact with the PUI's direct contacts; (iii) Environmental - individuals

   who spent time in facility rooms that may have been contaminated by the PUI (i.e. possible

   fomite or aerosol transmission). Each unique interaction is summarized regarding the time of

   day, duration, and location. All three types of contacts are then classified as Priority 1 or

   Priority 2 contacts (**Figure 3**).

2. Line listing tool: digitized respiratory line listing tool to store and track infection data.

3. Decontamination tool: identify all of the confined areas (suites, bathrooms, offices) and

   common areas that the PUI visited in the facility -- including the day, time, and duration. The

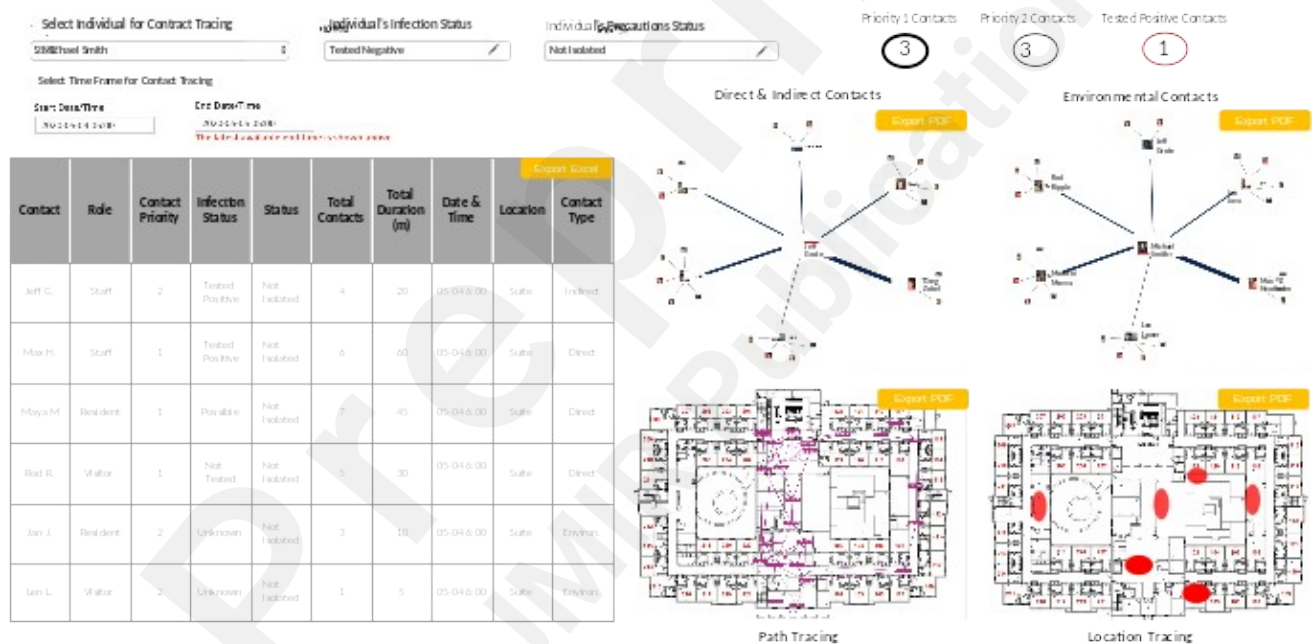   high-touch surfaces in these rooms can then be cleaned and disinfected.
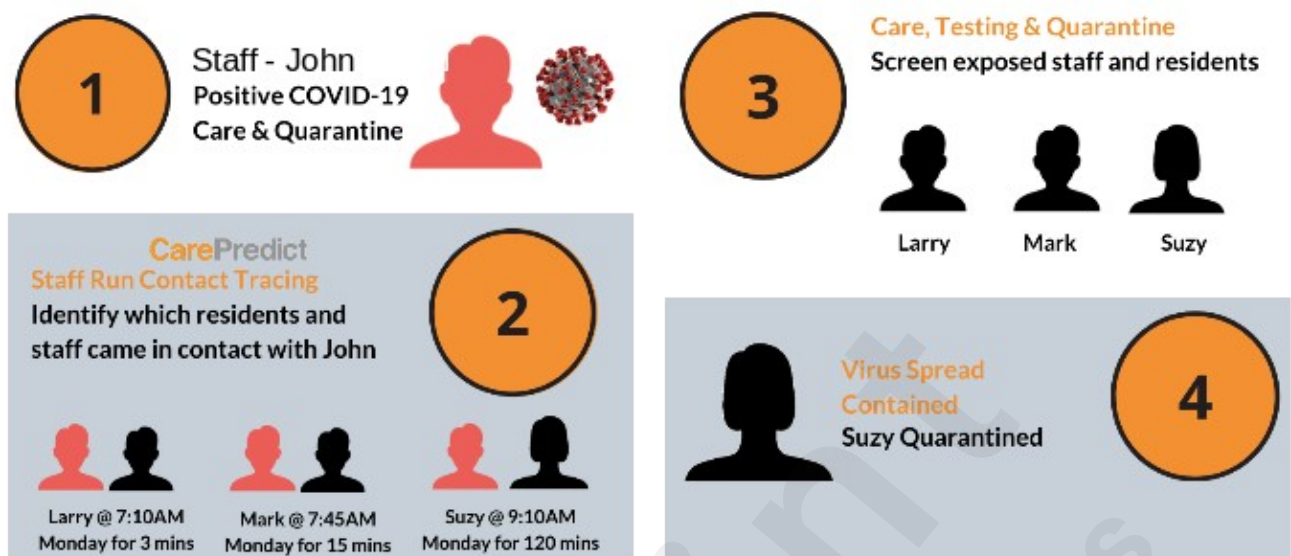
Figure 3. PinPoint digital contact tracing. A. Schematic of general process and B. Sample screenshot.

Simulation model

We developed a specialized Susceptible-Exposed-Infectious-Recovered (*SEIR*)-type compartmental

model to simulate the dynamics of propagation, disease transmission, and containment of SARS-

CoV-2 cases in LTC facilities.[48] In this model, individuals within the LTC facility (residents and

staff) are separated into mutually exclusive groups, or compartments based on their disease state:

susceptible (*S*), exposed (*E*), infected (*I*), quarantined (*Q*), and deceased (*D*). Infected individuals

were further segmented into two distinct groups: presymptomatic (I_P) and symptomatic infectious

individuals (I_S). The decoupled compartments include deceased (D) and quarantined individuals (Q)

from the (E, I_P, or I_S) compartments. The model assumes no demography, such that the population

size is constant, denoted by N. The facility was assumed to have a population of 120 persons,

consisting of 80 residents and 40 staff. A schematic representation of the model is provided in

Figure 4. The population dynamics are modeled by the following system of differential equations:

$$\frac{dS}{dt} = -\frac{\beta_p S I_P}{N} - \frac{\beta_s S I_S}{N}$$

$$\frac{dE}{dt} = \frac{\beta_p S I_P}{N} + \frac{\beta_s S I_S}{N} - \tau E - \Omega i \frac{\omega}{\delta} E$$

$$\frac{dI_P}{dt} = \tau E - \alpha I_P - \Omega i \frac{\omega}{\delta} I_P$$

$$\frac{dI_S}{dt} = \alpha I_P - \frac{\omega}{\delta} I_S$$

$$\frac{dQ}{dt} = \frac{\omega}{\delta}(E + I_P + I_S) - \mu Q$$

$$\frac{dD}{dt} = \mu Q \ .$$

where $N = S + E + I_P + I_S + Q + D$.

The transmission parameters, β_p, and β_s, represent the transmission rate for pre-symptomatic and

symptomatic individuals, τ is the mean latent period, α is the difference in latent and incubation

period, where α = (incubation period - τ). The following parameters varied depending on the

intervention approach: Ω_i is an intervention on/off parameter, ω is the intervention traced contact

probability, δ is the time delay to trace, where ω/δ is the rate at which a contact trace is quarantined,

and μ is the death rate. For this model, we assumed that once an individual is quarantined, all staff

would wear personal protective equipment (PPE) when interacting with residents, and thus no further

transmission would occur between quarantined and susceptible individuals.

The model was developed to assess the performance, defined as the number of cases and

resultant deaths, for several intervention types: digital contact tracing, manual contact tracing,

symptom-based mapping, PCR testing, and no intervention. **Table 1** contains the intervention

parameters and assumptions used in the model. For no intervention, β is set to average contacts per day from the facility. For intervention, $\beta_s = \beta_p/2$. For symptom mapping, we assume that only symptomatic individuals are quarantined but pre-symptomatic individuals are not ($\Omega = 0$). The initial time delays (δ) for each intervention method were as follows: symptom-based mapping (1 day), manual contact tracing (2 days), swab PCR (1 day), and digital contact tracing (0.1 days). Simulations were also conducted where the time delay parameter was adjusted in order to assess the impact that time delay has on interventional performance.
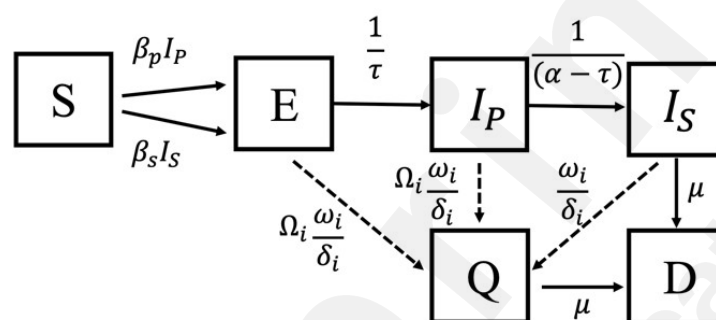

Figure 4. Schematic representation of infection and intervention model for COVID-19 in LTC facilities. Susceptible-Exposed-Infectious-Recovered (*SEIR*)-type compartmental model to simulate the dynamics of propagation, disease transmission, and containment of SARS-CoV-2 cases in LTC facilities.[48]   Individuals within the LTC facility (residents and staff) are separated into compartments based on their disease state: susceptible (*S*), exposed (*E*), infected (*I*), quarantined (*Q*), and deceased (*D*). Infected individuals were further segmented into two distinct groups: presymptomatic (I_P) and symptomatic infectious individuals (I_S). The decoupled compartments include deceased (*D*) and quarantined individuals (*Q*) from the (*E*, I_P, *or* I_S) compartments. The model assumes no demography, such that the population size is constant, denoted by *N*. The transmission parameters, β_p, and β_s, represent the transmission rate for pre-symptomatic and symptomatic individuals, τ is the mean latent period, α is the difference in latent and incubation period, where α = (incubation period - τ). The following parameters varied depending on the intervention approach: Ω_i is an intervention on/off parameter, ω is the intervention traced contact probability, δ is the time delay to trace, where ω/δ is the rate at which a contact trace is quarantined, and μ is the death rate.

Table 1: Parameters for compartmental infection and intervention model

Name	Symbol	Description	Central value	Range	References
Transmission rate	β_p	Infectious transmission rate for pre-	0.52 day^{-1}	0.5 -1.5 day^{-1}	[49], fit data

(presymptomatic)		symptomatic individuals			[15], [34]
Transmission rate (symptomatic)	β_s	Infectious transmission rate for symptomatic individuals. Assume half the contacts.	$\beta_P/2$ day^{-1}	0.5 -1.5 day^{-1}	[15, 49], [34]
Latency period	τ	Time from infection to infectious	4 days	3 - 5 days	[11, 16, 24-27]
Incubation period	α	Time from infection to symptomatic	8 days	2 - 14 days	[11, 16, 24-27]
Death rate	μ	Death rate	0.02 days	0.001 - 0.1	[34]
Intervention function Target	Ω_i	Manual Contact Tracing Swab PCR testing Digital Contact Tracing Symptom mapping No intervention	1 1: I_P & I_S, 0: E 1 0 0		
Symptom mapping trace rate	ω_s	Probability of traced contact by tracing symptomatic individuals	0.6		[34]
Manual contact tracing rate	Ω_m	Probability of traced contact by tracing symptomatic individuals	0.7		[50]
Swab PCR testing rate	Ω_m	Probability of traced contact by tracing symptomatic individuals	0.7		[34]
Digital contact tracing rate	ω_d	Probability of traced contact individuals	0.9		This study
Time delay to trace	δ	Symptom mapping	1 day		Ref
		Manual contact tracing	2 days		[42]
		PCR test	1 day		Ref
		Digital Contact Tracing	Hours		This study

Results

System Implementation

An example of implementation and workflow for the CarePredict PinPoint digital contact tracing system is provided in **Figure 5**. The process could work in the following manner. First, a positive COVID-19 case, defined as a person under investigation (PUI) is confirmed, immediately isolated, symptoms monitored, and hospitalized if necessary. Data for the PUI would then be inputted into the Pinpoint software respiratory line listing tool: A. case demographic; B. case location; C. signs and

symptoms; D. diagnostics; and E. outcome during outbreak. This line list date is then provided to the public health authorities (PHA) so they can begin manual contact tracing processes. Next, the digital contact tracing tool would be executed to identify the individuals that came in contact with the PUI over the past 14 days. The contacts are classified as either Priority 1 (High risk exposures, HREs) or Priority 2 (Low risk exposures, LREs), and staff would provide the necessary next steps of care. The Priority 1 contacts would be immediately quarantined, and their symptoms monitored, and the Priority 2 contacts would be monitored and provided safety instructions regarding physical distancing, rigorous hand hygiene, and respiratory etiquette. For safety precautions, the temperature of all contacts would be measured to see if the persons have a fever. [51] If signature or non-specific symptoms are not observed for 14 days then monitoring is stopped. PCR testing should be conducted on all exposed contacts (both symptomatic and asymptomatic) to determine if infected by SARS-CoV-2 or another pathogen. After completing the contact tracing runs, the decontamination tool would be used determine the rooms and areas in the facility that may be in infected and require cleaning.
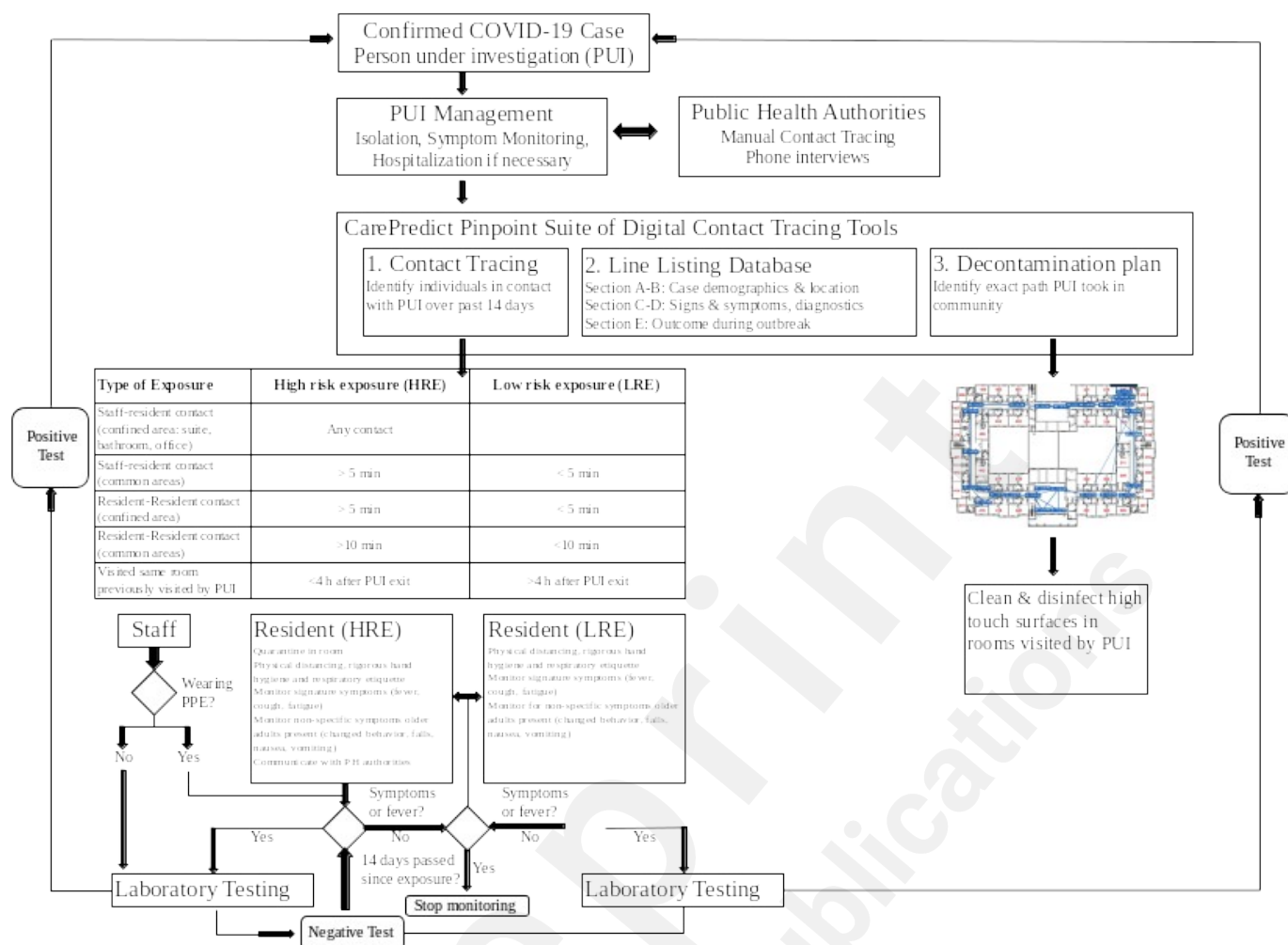
Figure 5. Sample representation for integrating CarePredict's PinPoint system and software into a long-term care (LTC) facility's COVID-19 risk assessment workflow. General workflow diagram developed to be consistent with those proposed by ECDC.[42]

Simulation Model

Asymptomatic SARS-CoV-2 infected cases contributed to the rapid spread in several LTC facilities [13, 14], and conventional methods were inadequate to control those outbreaks. To assess the impact that presymptomatic cases have on facility spread, we used our model to simulate and compare transmission for two initial conditions: one seeded with 10 presymptomatic cases and the other seeded with 10 symptomatic cases. The simulation results for each intervention group are presented in **Figure 6A**. For all intervention groups, more cases and greater infection spread is observed with seeding of presymptomatic cases (full lines) versus symptomatic cases (dotted lines). Symptom-based monitoring alone was the least effective intervention method, and at the end of a 40 day

simulation resulted in nearly 50% more cases than other interventional groups. Digital contact

tracing provided the most effective intervention control. Five days after presymptomatic seeding,

digital contact tracing yielded 5% and 7% fewer cases than PCR testing and manual contact tracing,

respectively. After 40 days, the digital contact tracing provided 6% and 12% fewer cases than PCR

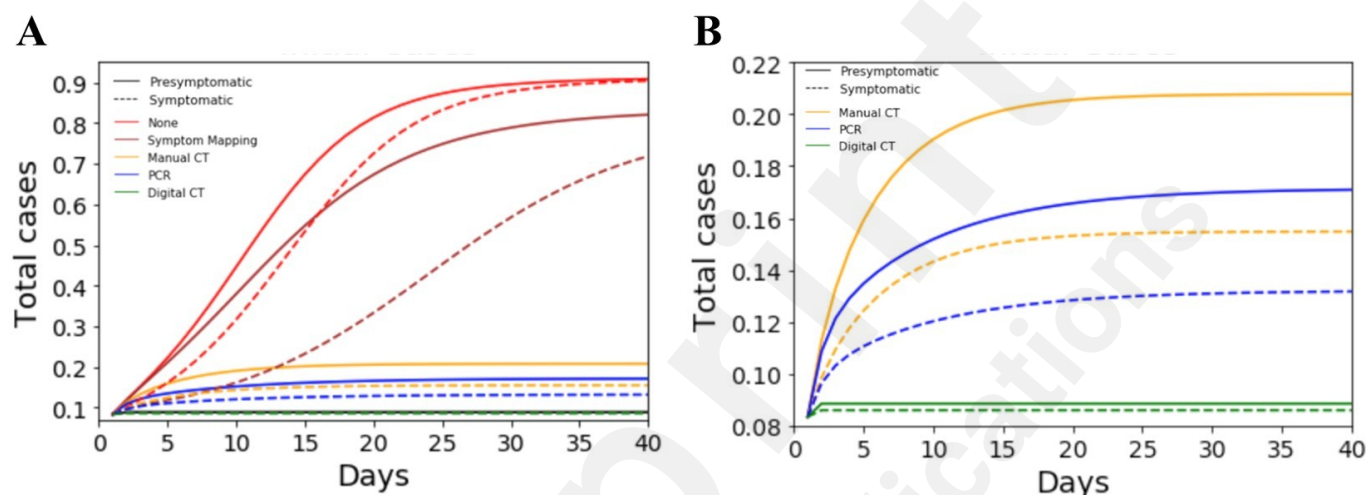testing and manual contact tracing, respectively (**Figure 6B**).

Figure 6. Assessing the impact of presymptomatic cases on facility spread. Simulations were performed to compare transmission and interventional control for two initial seeding conditions: presymptomatic (filled colored lines: 10 presymptomatic and 0 symptomatic cases); symptomatic (dotted colored lines: 0 presymptomatic and 10 symptomatic cases). Simulations were performed to measure the number of total cases as a function of time for each intervention group: digital contact tracing, PCR testing, manual contact tracing, symptom-based monitoring, and no intervention. A. Total cases over time for each intervention group and initial seeding condition. B. Total cases over time for manual contact tracing, PCR testing, and digital contact tracing.

To quantify control success for each intervention group, simulations were performed using an initial

seeding condition of 10 cases, 40% asymptomatic and 60% symptomatic cases. These conditions

were selected based best estimates provided by the CDC. [34] The simulation results for each

intervention group are presented in **Figure 7**. Symptom-based monitoring alone was the least

effective intervention method, resulting in nearly 60% more cases than the other interventional

groups (**Figure 7A**). Digital contact tracing provided the most effective intervention control,

resulting in the fewest number of new cases and deaths (**Figure 7B**). Direct contact tracing achieved

22%, 3%, and 2% fewer deaths than symptom-based monitoring, manual contact tracing, and PCR

testing methods, respectively. The data shows that with no intervention, 26% of the total cases result

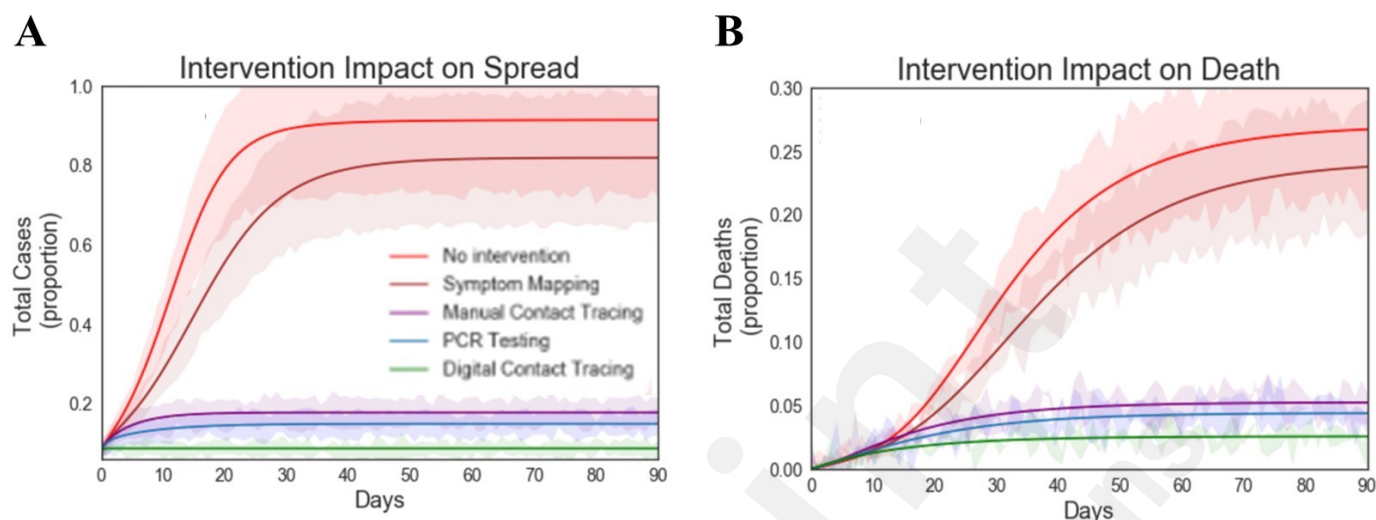in death, which is consistent with observed case infection fatalities in LTC facilities. [3]

Figure 7. Quantifying control success for each intervention group. A. Total cases (proportion) over time. B. Total deaths (proportion) over time. Simulations were performed for all intervention groups using initial seeding conditions: 10 cases (40% presymptomatic and 60% symptomatic cases). Time delay to trace for digital contact tracing (0.1 days), symptom-based mapping (1 day), manual contact tracing (2 days), and PCR testing (1 day). Simulations were performed to measure the total cases and deaths as a function of time for each intervention group: digital contact tracing, PCR testing, manual contact tracing, symptom-based monitoring, and no intervention.

Digital contact tracing software requires minimal human resources to instantaneously execute, and

thus has minimal time delays. However, symptom-based mapping, manual contact tracing, and PCR

testing are labor-intensive and have intrinsic time delays. In previous simulations, we optimistically

assumed that symptom-based mapping, manual contact tracing, and PCR testing could be performed

quickly with 1, 2, and 1 day time delays, respectively. In order to assess the impact that delayed

tracing has on intervention success, we conducted simulations where we delayed the tracing time for

each group by 2 days (**Figure 8**). The data shows that the increased delay in time to trace resulted in

increases in cases and deaths for all intervention groups. Due to the increased delays in time to trace,

PCR testing is now less effective than manual contact tracing. This result illustrates the importance

of rapid, frequent PCR testing and monitoring. Exposed individuals PCR tests typically are not

positive during their latency period, thus multiple followup tests must be performed to ensure they

are positive COVID-19 cases. Thus, if only individuals with positive PCR tests results are being isolated, then the cases that are infected, not yet infectious, and not quarantined could continue to infect others in the facility.
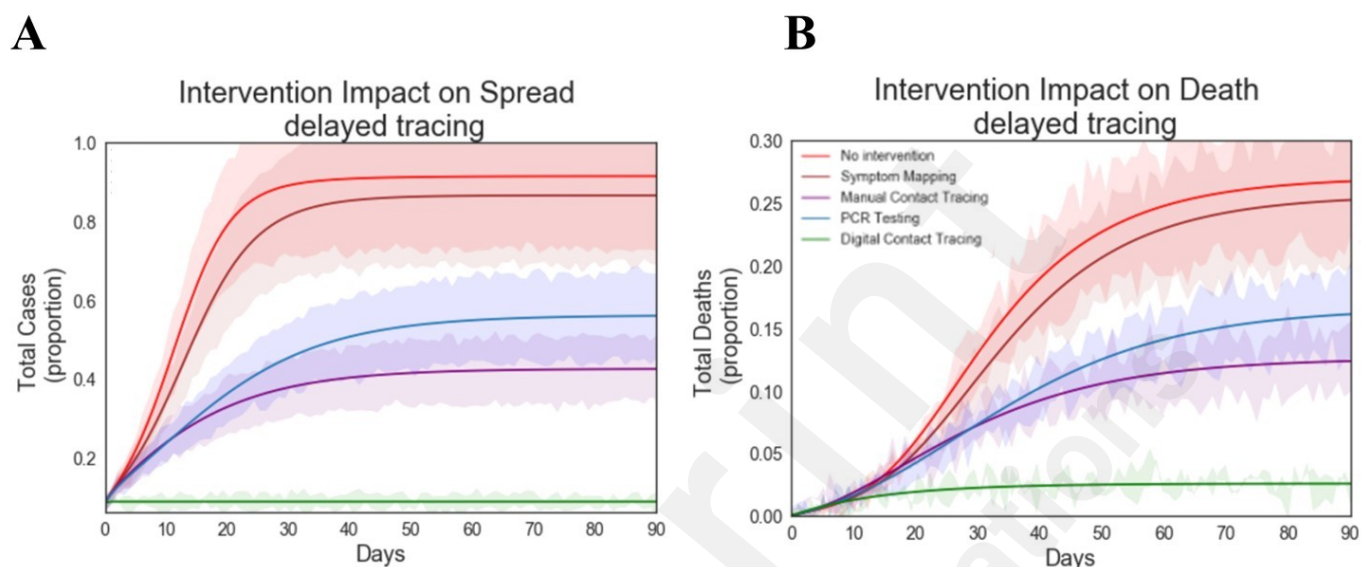

Figure 8. Effect of tracing delays on intervention performance. A. Total cases over time. B. Total deaths over time. Simulations were performed for all intervention groups using initial seeding conditions: 10 cases (40% presymptomatic and 60% symptomatic cases). Time delay to trace for digital contact tracing (0.1 days), symptom-based mapping (3 days), manual contact tracing (4 days), and PCR testing (3 days). Simulations were performed to measure the number of total cases and deaths as a function of time for all intervention groups: digital contact tracing, PCR testing, manual contact tracing, symptom-based monitoring, and no intervention.

A series of simulations were performed to understand the impact that intervention efficacy (probability of tracing a contact) and delay have on control success (**Figure 9**). The data shows that as the intervention efficacy (Ω) increases from 0 to 0.6, the number of cases drops sharply from 1.0 down to 0.15. (**Figure 9A**). Using a fixed time delay of 1 day, the number of total cases continues to drop with increases in intervention efficacy (Ω) from 0.6 to 1.0 but the reduction is less because the time delay is short (**Figure 9B**). The data shows that once an efficacy of 60% is achieved, only modest improvements in control can be achieved by improving the probability of tracing further. To assess the impact that intervention delay has on spread, simulations were conducted varying the time delay between 0 and 4 days, and assuming all interventions had an intervention efficacy of 70%

(**Figure 9C**). The data shows that increases in delay intervention time result in sharp increases in the number of total cases. Increasing the delay time from 1 day to 2, 3, and 4 days resulted in increases in total cases by 10%, 25%, and 45%. Clearly the delay time has significantly more impact on intervention success than interventional efficacy, assuming the probability of tracing exceeds 60%.
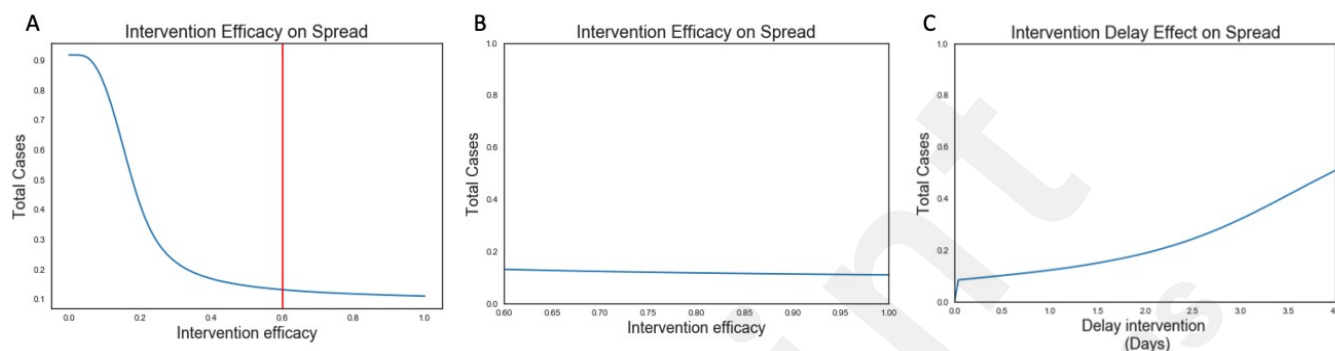

Figure 9. Impact of intervention efficacy and delay time on intervention success. A-B. Total cases as a function of intervention efficacy. C. Total cases as a function of intervention delay time (days).

Discussion

Over the past few months, rapid and widespread transmission of SARS-CoV-2 has been observed in numerous LTC facilities in the U.S. and in many countries across the world [13, 14, 23] As a result, residents of LTC facilities have been disproportionally impacted by SARS-CoV-2, and have accounted for over 40% of all COVID-19 fatalities worldwide. (**Supp. Figure 1**). [3, 52] Symptoms-based monitoring fails to identify asymptomatic infectious cases and slow manual contact tracing methods have proven inadequate for controlling SARS-CoV-2 transmission in LTC facilities.[6, 13-15, 23, 40] In this study, describe the development of a new digital contact tracing system designed for use in LTC facilities. Our computer simulation results comparing different intervention approaches suggest that this system shows promise to be an effective tool to control COVID-19 outbreaks in LTC facilities.

Principal Findings

In this study, we developed an epidemic compartmental model that was specifically parameterized to

quantify SARS-CoV-2 transmission and control in LTC facilities. We used the model and considered various scenarios to assess the effectiveness of several intervention groups to control outbreaks: no intervention, symptom-based monitoring, PCR testing, manual contact tracing, and digital contact tracing. Under all conditions tested, the digital contact tracing system outperformed all intervention groups, achieving reduced SARS-CoV-2 spread, fewer total cases, and fewer fatalities. Most importantly, we show that the most critical and sensitive parameter of the model is the time delay. All conventional control methods (symptom-based monitoring, manual contact tracing, and PCR testing) except digital contact tracing have intrinsic time delays that cannot be compensated for with increases in efficiency. We conducted several simulations where we increased each interventional group's probability of tracing a contact, and the results indicated that the control performance still could not reach the level achieved by digital contact tracing. Thus, the primary advantage of automated digital contact tracing methods is the speed at which potentially infectious contacts (both symptomatic and asymptomatic) can be instantly identified, classified, isolated and tested. Given the high proportion of asymptomatic infections, the ability to quickly identify and test potentially infected persons before they show symptoms is key to preventing future transmission in LTC facilities.

Results from our simulations indicate that symptom-based screening alone was the least effective intervention group, resulting in 50-60% greater cases and 10-20% more deaths than the other methods (Figures 6-8). A limitation of symptoms-based monitoring methods, such as temperature monitoring for a fever, is that presymptomatic secondary cases are missed. In LTC facilities asymptomatic cases are equally prevalent and infectious as symptomatic cases, and thus can be major contributors to COVID-19 outbreaks in LTC facilities. [13, 14, 16, 25, 39] Our data also suggests that symptom-based monitoring alone has intrinsic time delays due to time required for infected persons to both exhibit symptoms and then be identified by facility staff. To complicate matters, evidence is emerging that many older adults may not actually present the signature COVID-

19 symptoms (ie. fever, cough, shortness of breath). [14, 17, 53] Due to their blunted immune response systems and/or underlying chronic conditions, which may mask fever and acute illness, older adults may present atypical, non-specific, symptoms when ill with COVID-19, including increased falls, changes in activity and behavior (such as sleeping more and eating less), impaired mobility, malaise, fatigue, nausea, and even vomiting. [14, 17] Thus, staff may require more time and use lower thresholds for suspicion to identify infected older adults that exhibit subtle symptoms. Such delays may translate into further spread of infection in the facility.

Manual contact tracing is a useful core disease control that is a key part of our country's multipronged approach to mitigate COVID-19 transmission[41]. Estimates indicate that a large workforce of 300,000 tracers will be required for adequate tracing in the U.S. (nearly 1 tracer per 1000 people)[54]. The manual tracing process is error-prone and slow because it requires a human tracer to interview new cases (~2 hours/interview), and then list, classify, and follow-up with each contact (~1 h/call/contact). Results from our simulations indicate that the time delays created by manual processes render the method less effective in LTC facilities than digital contact tracing methods. We found that digital contact tracing methods resulted in 12% fewer cases (**Figure 6**) and 3% fewer deaths than manual contract tracing. As a result, manual contact tracing approaches will need to be supplemented with other rapid and efficient control measures. There are several additional challenges with using manual contact tracing alone in the LTC setting. First, an infected resident or staff member may have 10-30 close contacts, and estimates indicate that between 6 and 15 tracers require 12-24 h to fully trace one case. [42, 43, 55] The delays created by this process gives secondary contacts more time to transmit the virus even further in the facility. Second, manual contact tracing relies on humans both for data collection and data entry. This increases the potential for inaccurate or incomplete results due to human error. Accurate manual contact tracing requires the case to remember and report all contacts made over the past 14 days. In the LTC setting, many of the residents may be suffering from memory impairment or dementia, and thus they may forget many of

their contacts. The digital contact tracing system described in this study can automatically identify all

of the contacts for a case, and can be used to help augment manual contact tracing efforts performed

by public health authorities.

The most commonly used and reliable test for diagnosing SARS-CoV-2 infected cases is the

reverse transcription-polymerase chain reaction (RT-PCR) test. PCR tests measure viral RNA, are

performed using a nasopharyngeal, throat or saliva swabs, and take 1-2 days to process. PCR tests

can effectively measure infection in symptomatic COVID-19 persons, but are less likely to detect

infection during the case's latent period when they are presymptomatic. [16, 24] The results from our

simulation indicate that PCR testing was an effective control method for rapidly identifying infection

and minimizing transmission. In order to be highly effective, universal, serial (weekly or daily) PCR

testing should be implemented on both symptomatic and asymptomatic exposed contacts. In a recent

study, the authors investigated the benefit of serial RT-PCR testing of residents and staff at a LTC

facility after an initial COVID-19 case was diagnosed [39]. Dora *et al.* showed that after the first

case was identified, nineteen residents tested positive for SARS-CoV-2 (73% were asymptomatic)

and were rapidly transferred to an isolated ward to reduce further transmission. [39] One issue with

daily, universal testing at a LTC facility is the expense. PCR tests are expensive ($150 per test), so

daily testing at a 120 bed facility would cost $18,000. Frequent PCR testing for all nursing home and

LTC residents is reported to be unsustainable, where one-time tests would cost the industry $672

million. [56] Thus, to date, many LTC facilities have performed PCR tests on only symptomatic

COVID-19 cases. Given the proportion asymptomatic cases, we propose that digital contact tracing

systems could be used to identify all high priority possibly infectious contacts that should be selected

for PCR testing. This approach would be a cost-effective and effective method to control COVID-19

outbreaks.

Comparisons with Prior Work

Several previous studies describe the development of smartphone app-based, digital contact tracing tools applied to the current COVID-19 pandemic. [45, 46] Digital contract tracing apps may be useful tools to help mitigate the spread of SARS-CoV-2 for the general population; however, they have considerable privacy risks, and need to be widely adopted in order to effective. Smartphone-based approaches using apps may find limited utility in nursing homes and LTC facilities for several reasons. First, LTC residents are typically older adults, and only 31% of adults over the age of 75 and 17% of adults 80+ report owning a smartphone. [47] Second, in many LTC facilities, staff are not permitted to use a smartphone during the work day. Finally, smartphone-based approaches use Bluetooth technology which transmits through walls and doors, can result in false positives. Due to these limitations, digital contact tracing systems built specifically for LTC facilities have significant advantages.

Limitations

There are several limitations of this study. First, the computational models that we developed did not incorporate the potential contribution that an individual's underlying conditions may have on SARS-COV-2 infection, transmission parameters, and death rate. Since the impact of such conditions is not well-characterized, and empirical data is currently not available, we were unable to include these impacts in the model. However, it is well established that older adults are disproportionally affected by chronic conditions, and when such persons are infected suffer more severe COVID-19-associated illness. [19, 20] Richardson *et al.* found that 94% of patients hospitalized with COVID-19 exhibited one comorbidity [21], and studies indicate that 94% of COVID-19 patient deaths, 78% of intensive care unit (ICU) admissions, and 71% of non-ICU hospitalizations had at least one comorbidity. [57] The most common comorbidities contributing to hospitalization were hypertension (56.6%), obesity (41.7%), and diabetes (33.8%).[21] Studies on the effect of multiple co-morbidities on adults age 85 and older indicate the following: (i) COVID-19 hospitalizations: hypertension (38%), diabetes and

hypertension (22%), and Chronic obstructive pulmonary disease (COPD) and hypertension (10%);

(ii) COVID-19 deaths: hypertension (37%), diabetes and hypertension (23%), COPD and

hypertension (9%), and COPD, diabetes and hypertension (8%). [58] It is entirely possible that older

adults with specific underlying comorbidities or combination of particular comorbidities may exhibit

varying infection, transmission, and death rates. As more data becomes available and these

relationships are better characterized, we plan to incorporate them into models that we develop in

future studies.

Second, the digital contact tracing system described in this manuscript is currently in use by

several LTC facilities in the U.S. These facilities are reporting early control success with the system;

[59] however, a large enough sample size of empirical data has not been collected to date. Thus, the

preliminary empirical results were not compared to those generated with our computer simulation

models. Once a sufficient sample size of empirical data is collected using this system at LTC

facilities, we plan to conduct future studies to compare these findings versus the results generated by
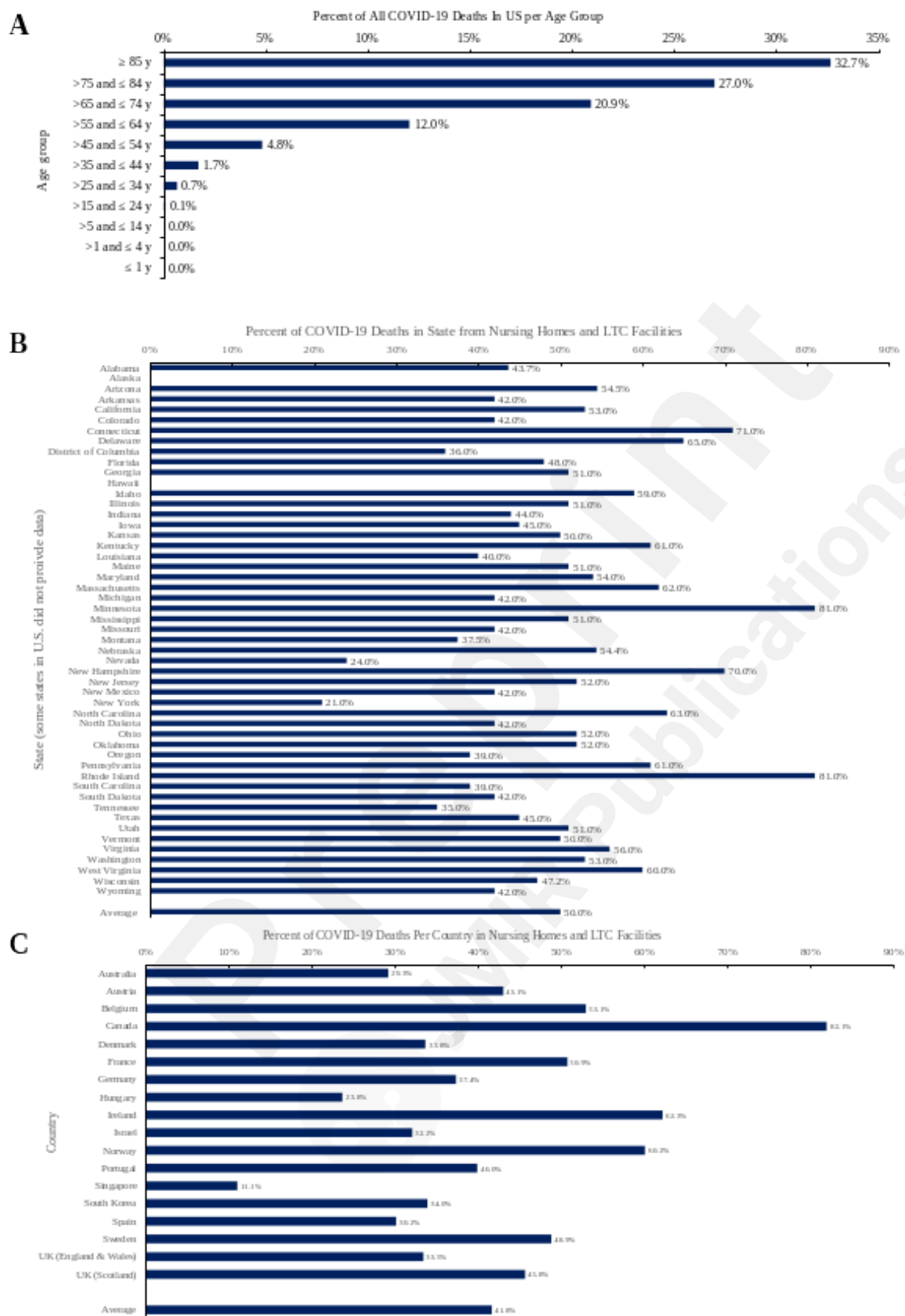
computer simulation models.

Conclusion

Our digital contact tracing system allows users to rapidly identify and then isolate close contacts, to

store and track infection data in a respiratory line listing tool, and to identify contaminated rooms.

Our simulation results suggest that digital contact tracing allows for rapid and effective identification

and containment of potentially infected contacts. This digital contact tracing system shows promise

as effective tool to control COVID-19 outbreaks. At the beginning of this pandemic, many facilities

implemented strict lockdown measures, which included prohibiting outside family visitors, closing

community dining rooms, and reducing social activities and events. These measures were required at

the time, but they negatively impacted many resident's physical, social, psychological, and emotional

health. As facilities prepare to re-open to outside visitors in the upcoming months, digital contact

tracing systems will allow them to do so in a surgical, cost-effective manner that both controls outbreaks while also safely giving residents back the life they once had before this pandemic hit.

Conflicts of Interest

Gerald J. Wilmink, Ilyssa Summer, David Marsyla, Jeffrey Grote, Greg Zobel, Satish Movva are employees of CarePredict.

Supplemental Figures

A

Percent of All COVID-19 Deaths In US per Age Group

B

Percent of COVID-19 Deaths in State from Nursing Homes and LTC Facilities

C

Percent of COVID-19 Deaths Per Country in Nursing Homes and LTC Facilities

Supplemental Figure 1. COVID-19 Deaths. A. Percentage of COVID-19 deaths by age group. [2, 3]. C. Percentage of COVID-19 deaths per state in LTC. Data aggregated and compiled from [3, 52]. C. Percentage of COVID-19 deaths per country in LTC. [60]

References

1. Zhu, N., D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu, P. Niu, F. Zhan, X. Ma, D. Wang, W. Xu, G. Wu, G.F. Gao, and W. Tan, *A Novel Coronavirus from Patients with Pneumonia in China, 2019.* New England Journal of Medicine, 2020. **382**(8): p. 727-733.

2. CDC. *Provisional Death Counts for COVID-19*. 2020; Available from: https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm.

3. The-Henry-J.-Kaiser-Family-Foundation, *State Data and Policy Actions to Address Coronavirus*. 2020.

4. Basu, A., *Estimating The Infection Fatality Rate Among Symptomatic COVID-19 Cases In The United States.* Health Affairs, 2020. **0**(0): p. 10.1377/hlthaff.2020.00455.

5. CDC, *Preliminary Estimate of Excess Mortality During the COVID-19 Outbreak — New York City, March 11–May 2, 2020. .* MMWR Morb Mortal Wkly Rep 2020, 2020. **69**: p. 603-605.

6. Hand, J., E.B. Rose, A. Salinas, X. Lu, S.K. Sakthivel, E. Schneider, and J.T. Watson, *Severe Respiratory Illness Outbreak Associated with Human Coronavirus NL63 in a Long-Term Care Facility.* Emerging infectious diseases, 2018. **24**(10): p. 1964-1966.

7. Lansbury, L.E., C.S. Brown, and J.S. Nguyen-Van-Tam, *Influenza in long-term care facilities.* Influenza and Other Respiratory Viruses, 2017. **11**(5): p. 356-366.

8. Living, N.-C.-f.-A. 2019; Available from: https://www.ahcancal.org/ncal/Pages/index.aspx.

9. L, H.-K., *Long-term Care Providers and Services Users in the United States, 2015-2016. .* Centers for Disease Control and Prevention, National Center for Health Statistics. , 2019. **43**.

10. NIC, *Seniors Housing Actual Rates Report 2Q2019* 2019.

11. Lauer, S.A., K.H. Grantz, Q. Bi, F.K. Jones, Q. Zheng, H.R. Meredith, A.S. Azman, N.G. Reich, and J. Lessler, *The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application.* Annals of internal medicine, 2020: p. M20-0504.

12. WHO. 2020; Available from: https://www.who.int/news-room/q-a-detail/contact-tracing.

13. Arons, M.M., K.M. Hatfield, S.C. Reddy, A. Kimball, A. James, J.R. Jacobs, J. Taylor, K. Spicer, A.C. Bardossy, L.P. Oakley, S. Tanwar, J.W. Dyal, J. Harney, Z. Chisty, J.M. Bell, M. Methner, P. Paul, C.M. Carlson, H.P. McLaughlin, N. Thornburg, S. Tong, A. Tamin, Y. Tao, A. Uehara, J. Harcourt, S. Clark, C. Brostrom-Smith, L.C. Page, M. Kay, J. Lewis, P. Montgomery, N.D. Stone, T.A. Clark, M.A. Honein, J.S. Duchin, and J.A. Jernigan, *Presymptomatic SARS-CoV-2 Infections and Transmission in a Skilled Nursing Facility.* New England Journal of Medicine, 2020.

14. Kimball A, H.K., Arons M, et al. , *Asymptomatic and Presymptomatic SARS-CoV-2 Infections in Residents of a Long-Term Care Skilled Nursing Facility — King County, Washington, March 2020.* MMWR Morb Mortal Wkly Rep, 2020.

15. Gandhi, M., D.S. Yokoe, and D.V. Havlir, *Asymptomatic Transmission, the Achilles' Heel of Current Strategies to Control Covid-19.* New England Journal of Medicine, 2020.

16. Wang, D., B. Hu, C. Hu, F. Zhu, X. Liu, J. Zhang, B. Wang, H. Xiang, Z. Cheng, Y. Xiong, Y. Zhao, Y. Li, X. Wang, and Z. Peng, *Clinical Characteristics of 138 Hospitalized Patients With 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China.* JAMA, 2020. **323**(11): p. 1061-1069.

17. Nikolich-Zugich, J., K.S. Knox, C.T. Rios, B. Natt, D. Bhattacharya, and M.J. Fain, *SARS-CoV-2 and COVID-19 in older adults: what we may expect regarding pathogenesis, immune responses, and outcomes.* GeroScience, 2020: p. 1-10.

18. Garg S, K.L., Whitaker M, et al. , *Hospitalization Rates and Characteristics of Patients Hospitalized with Laboratory-Confirmed Coronavirus Disease 2019 — COVID-NET, 14 States, March 1–30, 2020. ,* in *MMWR Morb Mortal Wkly Rep. .* 2020.

19. CDC, *Healthy Aging at a Glance* 2011.

20. Chronic Conditions Charts: 2015. Baltimore, M.C.f.M.M.S., *Chronic Conditions Charts.* 2015.

21. Richardson, S., J.S. Hirsch, M. Narasimhan, J.M. Crawford, T. McGinn, K.W. Davidson, and a.t.N.C.-R. Consortium, *Presenting Characteristics, Comorbidities, and Outcomes Among 5700 Patients Hospitalized With COVID-19 in the New York City Area.* JAMA, 2020.

22. Gardner, W., D. States, and N. Bagley, *The Coronavirus and the Risks to the Elderly in Long-Term Care.* Journal of Aging & Social Policy, 2020: p. 1-6.

23. McMichael TM, C.S., Pogosjans S, et al. , *COVID-19 in a Long-Term Care Facility — King County, Washington, February 27–March 9, 2020. .* MMWR Morb Mortal Wkly Rep, 2020. **69**: p. 339-342.

24. Sethuraman, N., S.S. Jeremiah, and A. Ryo, *Interpreting Diagnostic Tests for SARS-CoV-2.* JAMA, 2020.

25. Wölfel, R., V.M. Corman, W. Guggemos, M. Seilmaier, S. Zange, M.A. Müller, D. Niemeyer, T.C. Jones, P. Vollmar, C. Rothe, M. Hoelscher, T. Bleicker, S. Brünink, J. Schneider, R. Ehmann, K. Zwirglmaier, C. Drosten, and C. Wendtner, *Virological assessment of hospitalized patients with COVID-2019.* Nature, 2020.

26. Nishiura, H., N.M. Linton, and A.R. Akhmetzhanov, *Serial interval of novel coronavirus (COVID-19) infections.* International Journal of Infectious Diseases, 2020. **93**: p. 284-286.

27. Zhanwei, D., X. Xiaoke, W. Ye, W. Lin, J.C. Benjamin, and M. Lauren Ancel, *Serial Interval of COVID-19 among Publicly Reported Confirmed Cases.* Emerging Infectious Disease journal, 2020. **26**(6).

28. Stadnytskyi, V., C.E. Bax, A. Bax, and P. Anfinrud, *The airborne lifetime of small speech droplets and their potential importance in SARS-CoV-2 transmission.* Proceedings of the National Academy of Sciences, 2020: p. 202006874.

29. Hamner, L., *High SARS-CoV-2 Attack Rate Following Exposure at a Choir Practice - Skagit County, Washington, March 2020* MMWR Morb Mortal Wkly Rep, 2020. **69**(19): p. 606.

30. Santarpia, J.L., D.N. Rivera, V. Herrera, M.J. Morwitzer, H. Creager, G.W. Santarpia, K.K. Crown, D. Brett-Major, E. Schnaubelt, M.J. Broadhurst, J.V. Lawler, S.P. Reid, and J.J. Lowe, *Transmission Potential of SARS-CoV-2 in Viral Shedding Observed at the University of Nebraska Medical Center.* medRxiv, 2020: p. 2020.03.23.20039446.

31. Liu, Y., Z. Ning, Y. Chen, M. Guo, Y. Liu, N.K. Gali, L. Sun, Y. Duan, J. Cai, D. Westerdahl, X. Liu, K. Xu, K.-f. Ho, H. Kan, Q. Fu, and K. Lan, *Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals.* Nature, 2020.

32. van Doremalen, N., T. Bushmaker, D.H. Morris, M.G. Holbrook, A. Gamble, B.N. Williamson, A. Tamin, J.L. Harcourt, N.J. Thornburg, S.I. Gerber, J.O. Lloyd-Smith, E. de Wit, and V.J. Munster, *Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1.* New England Journal of Medicine, 2020.

33. DHS, *Estimated natural decay of SARS-CoV-2* 2020.

34. CDC. *COVID-19 Pandemic Planning Scenarios* 2020; Available from: https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html.

35. Nishiura, H., T. Kobayashi, T. Miyama, A. Suzuki, S.M. Jung, K. Hayashi, R. Kinoshita, Y. Yang, B. Yuan, A.R. Akhmetzhanov, and N.M. Linton, *Estimation of the asymptomatic ratio of novel coronavirus infections (COVID-19).* Int J Infect Dis, 2020. **94**: p. 154-155.

36. Ing, A.J., C. Cocks, and J.P. Green, *COVID-19: in the footsteps of Ernest Shackleton.* Thorax, 2020: p. thoraxjnl-2020-215091.

37. He, X., E.H.Y. Lau, P. Wu, X. Deng, J. Wang, X. Hao, Y.C. Lau, J.Y. Wong, Y. Guan, X. Tan, X. Mo, Y. Chen, B. Liao, W. Chen, F. Hu, Q. Zhang, M. Zhong, Y. Wu, L. Zhao, F. Zhang, B.J. Cowling, F. Li, and G.M. Leung, *Temporal dynamics in viral shedding and transmissibility of COVID-19.* Nature Medicine, 2020. **26**(5): p. 672-675.

38. Mizumoto, K., K. Kagaya, A. Zarebski, and G. Chowell, *Estimating the asymptomatic*

proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. Eurosurveillance, 2020. **25**(10): p. 2000180.

39.   Dora AV, W.A., Jatt LP, et al. , *Universal and Serial Laboratory Testing for SARS-CoV-2 at a Long-Term Care Skilled Nursing Facility for Veterans — Los Angeles, California, 2020. .* MMWR Morb Mortal Wkly Rep, 2020. **69**: p. 651-655.

40.   Roxby AC, G.A., Hatfield KM, et al. , *Detection of SARS-CoV-2 Among Residents and Staff Members of an Independent and Assisted Living Community for Older Adults — Seattle, Washington, 2020.* MMWR Morb Mortal Wkly Rep 2020;69:416–418, 2020. **69**: p. 416-418.

41.   Fraser, M., *A Coordinated, National Approach to Scaling Public Health Capacity for Contact Tracing and Disease Investigation* 2020.

42.   Control, E.C.f.D.P.a., *Resource estimation for contact tracing, quarantine, and monitoring activities for COVID-19 cases in EU/EEA.* 2020.

43.   Control, E.C.f.D.P.a., *Contact tracing: public health management of persons, including healthcare workers, having had contact with COVID-19 cases in the EU.* 2020: Stockholm.

44.   Hellewell, J., S. Abbott, A. Gimma, N.I. Bosse, C.I. Jarvis, T.W. Russell, J.D. Munday, A.J. Kucharski, W.J. Edmunds, F. Sun, S. Flasche, B.J. Quilty, N. Davies, Y. Liu, S. Clifford, P. Klepac, M. Jit, C. Diamond, H. Gibbs, K. van Zandvoort, S. Funk, and R.M. Eggo, *Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts.* The Lancet Global Health, 2020. **8**(4): p. e488-e496.

45.   Yasaka, T.M., B.M. Lehrich, and R. Sahyouni, *Peer-to-Peer Contact Tracing: Development of a Privacy-Preserving Smartphone App.* JMIR Mhealth Uhealth, 2020. **8**(4): p. e18936.

46.   Ferretti, L., C. Wymant, M. Kendall, L. Zhao, A. Nurtay, L. Abeler-Dörner, M. Parker, D. Bonsall, and C. Fraser, *Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing.* Science, 2020: p. eabb6936.

47.   Center, P.R., *Tech Adoption Climbs Among Older Adults.* 2017.

48.   Newman, M.E.J., *Networks.* Second edition. ed. 2018, Oxford, United Kingdom ; New York, NY, United States of America: Oxford University Press. xi, 780 pages.

49.   Li, R., S. Pei, B. Chen, Y. Song, T. Zhang, W. Yang, and J. Shaman, *Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2).* Science, 2020. **368**(6490): p. 489-493.

50.   Klinkenberg, D., C. Fraser, and H. Heesterbeek, *The effectiveness of contact tracing in emerging epidemics.* PloS one, 2006. **1**(1): p. e12-e12.

51.   Stone, N.D., M.S. Ashraf, J. Calder, C.J. Crnich, K. Crossley, P.J. Drinka, C.V. Gould, M. Juthani-Mehta, E. Lautenbach, M. Loeb, T. Maccannell, P.N. Malani, L. Mody, J.M. Mylotte, L.E. Nicolle, M.-C. Roghmann, S.J. Schweon, A.E. Simor, P.W. Smith, K.B. Stevenson, S.F. Bradley, and G. Society for Healthcare Epidemiology Long-Term Care Special Interest, *Surveillance definitions of infections in long-term care facilities: revisiting the McGeer criteria.* Infection control and hospital epidemiology, 2012. **33**(10): p. 965-977.

52.   FREEOP, *Nursing Homes & Assisted Living Facilities Account for 43% of COVID-19 Deaths.* 2020.

53.   Norman, R.E., N.M. Stall, and S.K. Sinha, *Typically Atypical: COVID-19 Presenting as a Fall in an Older Adult.* Journal of the American Geriatrics Society. **n/a**(n/a).

54.   ASTHO, *A National Plan to Enable Comprehensive COVID-19 Case Finding and Contact Tracing in US.* 2020.

55.   WHO, *Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19)* 2020.

56.   AHCA, *COVID-19 Testing for Nursing HOmes and Assisted LIving Communities* 2020.

57.   CDC_COVID19_RESPONSE_TEAM, *Preliminary Estimates of the Prevalence of Selected Underlying Health Conditions Among Patients with Coronavirus Disease 2019 — United States, February 12–March 28, 2020. .* MMWR Morb Mortal Wkly Rep, 2020. **69**: p. 382–

386.

58.   Network, E.H.R., *Prevalence of Comorbidities in COVID-19 Related Hospitalizations and Deaths*. 2020.

59.   Reuters, *Elderly Home Turns to Wearables for Contact Tracing, Sidestepping Apple-Google Limits*. 2020.

60.   Comas-Herrera A, Z.J., Litwin C, Hsu AT, Lane N and Fernández J-L *Mortality associated with COVID19 outbreaks in care homes: early international evidence.* . LTCcovid.org_International Long-Term Care Policy Network, CPEC-LSE 2020.